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The effects of field plot size on model-assisted estimation of aboveground biomass change using multitemporal interferometric SAR and airborne laser scanning data

Erik Næsset [a,*], Ole Martin Bollandsås [a], Terje Gobakken [a], Svein Solberg [b], Ronald E. McRoberts [c]

[a] Department of Ecology and Natural Resource Management, Norwegian University of Life Sciences, P.O. Box 5003, NO-1432 Ås, Norway
[b] Norwegian Forest and Landscape Institute, P.O. Box 115, NO-1431 Ås, Norway
[c] Northern Research Station, U.S. Forest Service, Saint Paul, MN, USA

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ABSTRACT

Remotely sensed data from airborne laser scanning (ALS) and interferometric synthetic aperture radar (InSAR) can greatly improve the precision of estimates of forest resource parameters such as mean biomass and biomass change per unit area. Field plots are typically used to construct models that relate the variable of interest to explanatory variables derived from the remotely sensed data. The models may then be used in combination with the field plots to provide estimates for a geographical area of interest with corresponding estimates of precision using model-assisted estimators. Previous studies have shown that field plot sizes found suitable for pure field surveys may be sub-optimal for use in combination with remotely sensed data. Plot boundary effects, co-registration problems, and misalignment problems favor larger plots because the relative impact of these effects on the models of relationships may decline by increasing plot size. In a case study in a small boreal forest area in southeastern Norway (852.6 ha) a probability sample of 145 field plots was measured twice over an 11 year period (1998/1999 and 2010). For each plot, field measurements were recorded for two plot sizes (200 m^2 and 300/400 m^2). Corresponding multitemporal ALS (1999 and 2010) and InSAR data (2000 and 2011) were also available. Biomass for each of the two measurement dates as well as biomass change were modeled for all plot sizes separately using explanatory variables from the ALS and InSAR data, respectively. Biomass change was estimated using model-assisted estimators. Separate estimates were obtained for different methods for estimation of change, like the indirect method (difference between predictions of biomass for each of the two measurement dates) and the direct method (direct prediction of change). Relative efficiency (RE) was calculated by dividing the variance obtained for a pure field-based change estimate by the variance of a corresponding estimate using the model-assisted approach. For ALS, the RE values ranged between 7.5 and 15.0, indicating that approximately 7.5–15.0 as many field plots would be required for a pure field-based estimate to provide the same precision as an ALS-assisted estimate. For InSAR, RE ranged between 1.8 and 2.5. The direct estimation method showed greater REs than the indirect method for both remote sensing technologies. There was clearly a trend of improved RE of the model-assisted estimates by increasing plot size. For ALS and the direct estimation method RE increased from 9.8 for 200 m^2 plots to 15.0 for 400 m^2 plots. Similar trends of increasing RE with plot size were observed for InSAR. ALS showed on average 3.2–6.0 times greater RE values than InSAR. Because remote sensing can contribute to improved precision of estimates, sample plot size is a prominent design issue in future sample surveys which should be considered with due attention to the great benefits that can be achieved when using remote sensing if the plot size reflects the specific challenges arising from use of remote sensing in the estimation. That is especially the case in the tropics where field resources may be scarce and inaccessibility and poor infrastructure hamper field work.

1. Introduction

1.1. Background

Reliable estimation of changes in forest carbon pools has become a prominent issue in forest inventory and remote sensing. Countries ratifying the Kyoto Protocol to the United Nations Framework Convention

* Corresponding author.
E-mail address: erik.naesset@nmbu.no (E. Næsset).

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on Climate Change are committed to report their emissions and removals of carbon dioxide, including emissions and removals in the land use and forestry sectors (UNFCCC, 2008). The United Nations Collaborative Program on Reducing Emissions from Deforestation and Forest Degradation in Developing Countries (UN REDD) (http://www.un-redd.org) was launched with the aim of contributing to the development of capacity for reducing emissions from loss of forest carbon in developing countries. Establishment of appropriate systems for estimating changes in carbon stocks is of vital importance for a successful implementation of REDD.

Field-based nationwide sample surveys, such as the national forest inventories in Europe and North America are the primary sources of data on aboveground biomass (AGB) and other carbon pools. Plot-based estimates of AGB are often not sufficiently precise for the intended purposes, and perhaps even more so for estimates of changes in AGB over time. Recent studies have shown that remotely sensed data can increase the precision of AGB estimates as well as AGB change estimates (McRoberts, Andersen, & Næsset, 2014; McRoberts, Bollandsås, & Næsset, 2014). One way to enhance the estimation is by using classifications of remotely sensed data for stratification (McRoberts, Gobakken, & Næsset, 2012; Næsset, Bollandsås, Gobakken, Gregoire, & Ståhl, 2013). Several other options exist as well. A commonly adopted strategy entails constructing a model of the relationship between observations of the variable of interest on field plots and the auxiliary variables derived from the remotely sensed data for the same plots. This model is then used to predict the variable of interest for all population elements for which the remotely sensed data are collected. The parameter of interest is estimated as the mean over the predictions, possibly adjusted for systematic deviations between observations and model predictions. The quality of fit of the model used in the estimation will influence the contribution of the remotely sensed data to reduce uncertainty of the estimate.

Airborne laser scanning (ALS) and interferometric synthetic aperture radar (InSAR) are among the two most promising remote sensing-based technologies to enhance estimates of AGB and AGB change because these sources can provide data that can be transformed to height-related forest canopy information which is highly correlated with AGB. While ALS can provide a smaller variance of mean AGB estimates compared to a pure field-based estimate by a factor of 2–6 (McRoberts, Andersen, et al., 2014), and typically around 5, the gain in precision with InSAR is more moderate. Næsset et al. (2011) reported a variance estimate of mean AGB for InSAR utilizing data from the Shuttle Radar Topography Mission (SRTM) that was smaller than the variance of a field-based estimate by a factor of 1.3. In the same study the variance of the ALS-assisted mean AGB estimate was smaller by a factor of 5.3. However, the InSAR variance estimate most likely did not reflect the full potential of InSAR to reduce uncertainties due to temporal inconsistency between the field data and the InSAR acquisition.

While larger costs may hamper widespread wall-to-wall application of ALS to enhance forest inventories, at least in developing countries in which labor costs currently are small, InSAR data from bi-static acquisitions are now globally available from the German Tandem-X mission. SAR also has the advantage of not being hampered by cloud cover because the longer wavelengths (3–60 cm) penetrate clouds. Persistent cloud cover is a problem in some tropical areas and limits the opportunities for all other remote sensing techniques, including ALS.

1.2. Modeling and estimating change with ALS and InSAR data

Although many studies on the contribution of ALS and InSAR to enhance estimates of AGB have appeared in the literature over the last 5–10 years, estimating AGB change rather than current stock with assistance of data from the same two remote sensing techniques is largely an unexplored area. Only a few studies on ALS-assisted estimation of change have been published (Andersen, Reutebuch, McGaughey, d'Oliveira, & Keller, 2014; McRoberts, Næsset, Gobakken, & Bollandsås, 2015; Næsset et al., 2013; Skowronski, Clark, Gallagher, Birdsey, & Hom, 2014), while evidence of the contribution of InSAR to enhance estimates of change in AGB is scarce (Solberg, Næsset, Gobakken, & Bollandsås, 2014). Consequently, there is also a lack of comparative studies on the contribution of various types of remotely sensed data to improve precision of change estimates. Such studies are needed in order to design cost-effective surveys.

1.2.1. ALS

In a recent review McRoberts, Bollandsås, et al. (2014) distinguish between the challenges associated with modeling change using ALS data and the estimation of the changes by applying the models. McRoberts et al. (2015) elaborated further on these aspects and identified two principle methods to modeling and estimation with ALS, namely (1) direct and (2) indirect methods.

The direct method entails constructing a model of the relationship between observations of AGB change and observations of ALS-derived auxiliary variables for the two dates in question. The auxiliary variables can either be variables from each individual date used in the same model (McRoberts et al., 2015) or variables calculated as the differences between corresponding variables from each date (Bollandsås, Gregoire, Næsset, & Øyen, 2013; McRoberts et al., 2015; Næsset et al., 2013; Skowronski et al., 2014). The model is then used to predict change for each population element, and mean change per unit area is estimated as the mean over population elements of model predictions, possibly adjusted to compensate for systematic model prediction errors.

The indirect method entails constructing a model of the relationship between observations of AGB and the auxiliary variables for each of the two dates individually (Bollandsås et al., 2013; McRoberts et al., 2015; Næsset et al., 2013; Skowronski et al., 2014). Mean change per unit area is estimated as the mean over population elements of the differences in the two model predictions, possibly adjusted to compensate for systematic model prediction errors.

Using statistically rigorous and analytically derived model-assisted estimators Næsset et al. (2013) and Skowronski et al. (2014) found that the direct method provided the most precise estimates of mean AGB change. So did also McRoberts et al. (2015) when using a modeling approach that allowed the greatest flexibility of the models. They all reported smaller variances of ALS-assisted mean AGB change estimates compared to pure field-based estimates by a factor of around 5–20. Allowing the individual ALS-derived auxiliary variables for each date to be included in the direct prediction models for change, rather than using the change in the auxiliary variables, improved the precision (McRoberts et al., 2015). Precision can potentially also be improved by stratifying on type of change (e.g. partial or complete removal of biomass and untouched). Especially for partial removal (thinning or degradation) there seems to be a great potential for improving the precision of change estimates by assisting the estimation with ALS data (Næsset et al., 2013).

1.2.2. InSAR

Modeling and estimating change with the assistance of auxiliary InSAR data raise some of the same principle issues as with ALS data. However, some unique challenges are also associated with InSAR change estimation. Because InSAR provides an absolute height value at the center of the SAR echo, which is located somewhere in the canopy, the elevation of the terrain must come from another independent source to facilitate computation of relative height of the canopy above the terrain. The relative height can subsequently be used as an auxiliary variable in the modeling and estimation. Availability of an independent digital terrain model (DTM) is therefore of fundamental importance. Thus, also indirect modeling and estimation of AGB change rest on the same fundamental requirement.

Direct modeling of change in AGB can be a viable method to circumvent the requirement of a DTM restricting application of the indirect method. Direct modeling would rely on the difference between absolute InSAR heights from the two dates without need for a DTM. To the very